IMAGE SEGMENTATION OF RETINAL VESSELS BY FUZZY MODELS

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ABSTRACT

Image segmentation of retinal vessels is an important and very challenging task in any automated system for the diagnosis of vascular conditions associated with diabetic retinopathy which is the most common complications of diabetes. In this paper we propose several fuzzy computational models for detecting retinal vessels in images which are subjected to inconsistent contrast and vague boundaries.

1. INTRODUCTION

Diabetic retinopathy affects up to 40% of patients with diabetes. In the early stages, it is generally asymptomatic, but as retinal perfusion decreases there may be progression to pre-proliferative and proliferative changes and risk of visual impairment. Prevention and early detection are essential as tight glycaemic and blood pressure control may delay onset or retard progression of retinopathy. Also, a number of other therapies including protein kinase C inhibitors are currently being evaluated for treatment of patients with evolving retinopathy. Annual eye screening is recommended for all patients with diabetes, and digital photography is rapidly becoming the standard method for this. Since around 7% of the adult population have diabetes, and much of the increase has been amongst older people with metabolic syndrome and a high risk of eye disease, the task of maintaining high quality eye screening on a population basis is a considerable one.

The detection and grading of retinopathy is both time consuming and repetitive, but requires a relatively high degree of skill and is subject to variability and error. Furthermore, although currently used grading systems do yield important prognostic information, they are semi-quantitative and therefore of limited use in documenting disease progression. A system to automate interpretation of retinal images could improve detection, be useful in comparing sequential images from the same patient, and in quality control. Furthermore, quantitative analysis would be useful in scientific studies relating to disease progression and the effect of interventions. Work in the early 1990s used digitised images from fluorescein angiograms and demonstrated the potential utility of automated interpretation [4]. However, angiography is an invasive procedure and not suitable for mass screening.

The focus of this paper is on the image segmentation of retinal vascular trees in patients with diabetes. In a recently published work [5], a methodology for segmenting the retinal vasculature and precisely quantifying (to subpixel level) vascular diameter has been developed. This method performs better than other described methods and should prove useful in quantifying the early changes associated with diabetes. However this technique assumes the information of approximate vessel center lines be given and therefore its main contribution is in vascular measurement, i.e. not segmentation. The importance of changes in retinal vascular calibre has been demonstrated recently in studies with an automated retinal vessel analyser: dynamic changes in response to visual and pharmacological stimuli can be measured over a short period of time. A portion of the retinal vasculature is selected for measurement and following baseline measurement a stimulus is delivered and serial images are acquired to assess changes in retinal vessel diameter. Using this equipment, impaired retinal vessel responses due to aging and to diabetes have been demonstrated [6]. This technique is very useful for short-term dynamic studies but could not readily be applied to large numbers of patients and also suffers from the disadvantage of only sampling a small part of the retinal vasculature.

2. FUZZY MODELS FOR SEGMENTATION OF RETINAL VESSELS

Let $U = [u_{nt}]$ be a matrix whose elements are memberships of $\mathbf{x}_t$ in the nth cluster, $n = 1, \ldots, N$, $t = 1, \ldots, T$. The

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fuzzy c-partition space for image $\mathbf{X}$ is the set of matrices U such that [1]

$$0 \le u_{nt} \le 1 \qquad \forall n,t, \qquad \sum_{n=1}^{N} u_{nt} = 1 \qquad \forall t,$$
$$0 < \sum_{t=1}^{T} u_{nt} < T \qquad \forall n \quad (1)$$

where $0 \le u_{nt} \le 1\ \forall n,t$ means it is possible for each $\mathbf{x}_t$ to have an arbitrary distribution of membership among the N fuzzy clusters.

$\mathbf{x}_t$ is assigned to a particular class $\mathcal{C}_n$ if

$$\mathcal{C}_n = \arg\max_n \ u_{nt}(\mathbf{x}_t) \quad (2)$$

To sharpen the fuzzy distribution, or in other word, to reduce the ambiguity in the classification, the image element is assigned to a fuzzy class if its membership grade is equal or greater than a certain threshold, that is [10]

$$\mathcal{C}_n = \arg\max_n \ u_{nt}(\mathbf{x}_t) \ge \mu_\theta \quad (3)$$

where μ_θ is the given fuzzy membership threshold.

We apply two fuzzy-partition models known as the fuzzy c-means and the fuzzy entropy clustering algorithms to compute two versions of the fuzzy membership matrix U. We describe the two clustering algorithms in the subsequent sections.

2.1. Fuzzy c-means partition

The FCM technique is based on minimization of the fuzzy squared-errors function

$$J(U,\mathbf{X}) = \sum_{n=1}^{N}\sum_{t=1}^{T} u_{nt}^m d_{nt}^2 \quad (4)$$

where $U = \{u_{nt}\}$ is a fuzzy c-partition of $\mathbf{X}$, $m > 1$ is a weighting exponent on each fuzzy membership u_{it} and controls the degree of fuzziness, and d_{nt} is the distance measure between $\mathbf{x}_t$ and $\mathbf{c}_n$. The basic idea of the FCM method is to minimize $J(U,\mathbf{X})$ on the assumption that matrix U identifies the good partition of the data.

The general FCM algorithm is summarized as follows.

1. Given a data set $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T\}$, where $\mathbf{x}_t = (x_{t1}, x_{t2}, \ldots, x_{tK}), t = 1,2,\ldots,T$.
2. Initialize membership values $u_{nt}, 1 \le t \le T, 1 \le n \le N$, at random
3. Given $\epsilon > 0$ (small real number).
4. Set $i = 0$ and $D^{(i)} = 0$. Iteration:
   (a) Compute cluster centers
   $$V(\mathbf{x}_t) = \mathbf{c}_n = \sum_{t=1}^{T} u_{nt}^m \mathbf{x}_t \Big/ \sum_{t=1}^{T} u_{nt}^m$$
   $$1 \le t \le T, 1 \le n \le N \quad (5)$$
   (b) Compute d_{nt} and $D^{(i+1)}$
   $$d_{nt} = \|\mathbf{x}_t - V(\mathbf{x}_t)\|_2 \quad (6)$$
   $$D^{(i+1)} = \frac{1}{TK}\sum_{t=1}^{T} d_{nt}^2 \quad (7)$$
   (c) Update membership values
   $$u_{nt} = \frac{1}{\sum_{k=1}^{N} \left(d_{nt}^2/d_{kt}^2\right)^{1/(m-1)}} \quad (8)$$
5. Set $D^{(i)} = D^{(i+1)}$ then $i = i+1$. Go to step (a) if
   $$\frac{D^{(i+1)} - D^{(i)}}{D^{(i+1)}} > \epsilon \quad (9)$$

2.2. Fuzzy entropy partition

The fuzzy entropy (FE) technique is based on minimisation of the following function [11]:

$$H(U,\mathbf{X}) = \sum_{n=1}^{N}\sum_{t=1}^{T} u_{nt} d_{nt}^2 + m_E \sum_{n=1}^{N}\sum_{t=1}^{T} u_{nt}\log u_{nt} \quad (10)$$

where $U = \{u_{nt}\}$ is a fuzzy c-partition of $\mathbf{X}$ as defined for fuzzy c-means partition, $m_E > 0$ controls the degree of fuzzy entropy, and d_{nt} has been previously defined. The basic idea of the FE technique is to minimize $H(U,\mathbf{X})$ such that matrix U identifies the good partition of the data.

The general fuzzy entropy algorithm is summarized as follows.

1. Given a data set $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T\}$, where $\mathbf{x}_t = (x_{t1}, x_{t2}, \ldots, x_{tK}), t = 1,2,\ldots,T$.
2. Initialize membership values $u_{nt}, 1 \le t \le T, 1 \le n \le N$, at random
3. Given $\epsilon > 0$ (small real number).
4. Set $i = 0$ and $D^{(i)} = 0$. Iteration:
   (a) Compute cluster centers
   $$V(\mathbf{x}_t) = \mathbf{c}_n = \sum_{t=1}^{T} u_{nt} \mathbf{x}_t \Big/ \sum_{t=1}^{T} u_{nt}$$
   $$1 \le t \le T, 1 \le n \le N \quad (11)$$

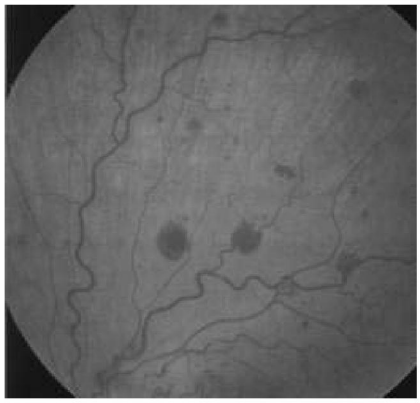

Figure 1. Original gray-scale image

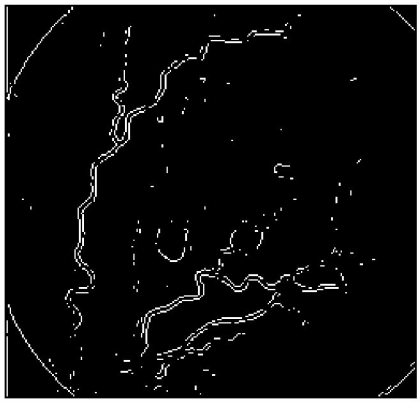

Figure 2. Edge detection using Sobel operator

(b) Compute d_{nt} and $D^{(i+1)}$

$$d_{nt} = \|\mathbf{x}_t - V(\mathbf{x}_t)\|_2 \tag{12}$$

$$D^{(i+1)} = \frac{1}{TK}\sum_{t=1}^{T} d_{nt}^2 \tag{13}$$

(c) Update membership values

$$\overline{u}_{nt} = \frac{1}{\sum_{k=1}^{N} e^{(d_{nt}^2 - d_{kt}^2)/m_E}} \tag{14}$$

5. Set $D^{(i)} = D^{(i+1)}$ then $i = i + 1$. Go to step (a) if

$$\frac{D^{(i+1)} - D^{(i)}}{D^{(i+1)}} > \epsilon \tag{15}$$

3. EXPERIMENTAL ANALYSIS

Figure 1 shows the retinal vascular trees in a patient with diabetes. Diabetic retinopathy (DR) can be divided into three

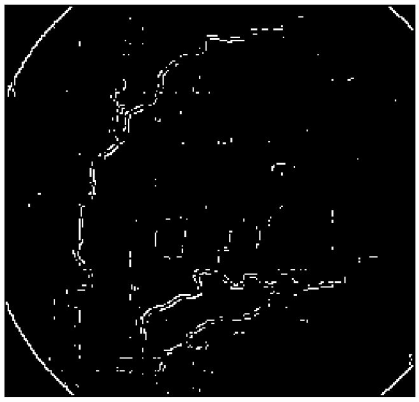

Figure 3. Edge detection using Roberts operator

Figure 4. Segmentation using Otsu's thresholding

clinical stages: simple retinopathy, preproliferative retinopathy, and proliferate retinopathy [2]. In the early stage, retinopathy is characterized by capillary wall thickening, pericyte loss, increased leucocyte adhesion to the vessal wall, and alteration in blood flow [9]. As the disease progresses, dot and blot hemorehages and hard exudate can be observed by ophthalmoscope examination [7]. We applied several edge detection techniques to mainly detect the retinal vessels and other retinal features shown in Figure 1. The results obtained from two popular edge detection techniques which are Sobel, and Roberts methods [12] are shown in Figures 2-3, respectively. However, both results are not so realiable due to many disconnected segments of the vascular trees.

Figure 4 shows the segmentation by Otsu's thresholding method. Figure 5 shows the segmentation using the FCM method based on two clusters, and the decision criterion expressed in (2). Figure 6 shows the same segmentation results obtained from: the FCM based on two clusters, with μ_θ=0.8 for the criterion given in (3), three clusters using (2); and the fuzzy entropy partition method.

The FCM using criterion (3) with a cut-off threshold

Figure 5. Segmentation using FCM without cut-off μ_θ

Figure 6. Segmentation using FCM (2 clusters, μ_θ=0.8), FCM (3 clusters), and fuzzy entropy partition

μ_θ=0.8 provided a better detection of the retinal blood vessels than the FCM using criterion (2); while performed equally with the modeling of three fuzzy clusters for the FCM and the fuzzy entropy method. The concept of having three clusters is to represent three inherent classes in medical and biological images : object, background, and fuzziness [10].

4. CONCLUSIONS

Although diabetic retinopathy is the most common cause of visual impairment in the non-elderly population, the most common cause of visual impairment in elderly people with diabetes is macular disease, to which diabetic patients are predisposed. Automated detection of degenerative changes has been achieved using scanning laser ophthalmoscope images. These lesions are almost invariably present in patients with age-related macular degeneration and while they are not directly responsible for visual loss, they do correlate with prognosis. Also, they need to be distinguished from hard exudates. No system reported to date has addressed the identification of new vessel formation. New blood vessels arise in areas of the macula with poor perfusion. Haemorrhage from these fragile structures and subsequent organisation of the blood clot leads to retinal detachment and blindness. Early detection of new vessels and treatment using autofluorescence [3] has been the motivation behind the development of diabetes eye screening programmes. New vessels are thin and highly irregular. Non-specialist clinicians find difficulty in identifying new vessels, and this often leads to inappropriate ophthalmological referral.

We have proposed some fuzzy models which can detect large retinal blood vessels. However, neither edge-detection based nor fuzzy-model based image segmentation methods can locate thin vessels. A possible solution to this problem will need further theoretical developments and is being under the investigation of our research team.

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